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厦门大学

# 硕士学位论文

# 基于稀疏表示的车标识别方法研究

# Vehicle Logo Recognition Based on Sparse Representation

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# 摘　要

车标识别技术融合了计算机视觉、模式识别与图像处理等多个研究方向，是当前智能交通领域的研究热点之一。现有的车标识别方法大多需要进行车标的精确定位，而车标普遍存在污损、光照、部分遮挡等情况，目前还没有一种有效的方法能够对这些车标进行准确定位，这在很大程度上影响了车标的识别率，也使得现有车标识别方法在实际应用中受到制约。

针对现有车标识别方法的不足，本文在深入研究稀疏表示理论的基础上，提出了基于稀疏表示的车标识别方法。由于稀疏表示能够对信号进行简洁的表示，而最简洁的表示往往具有天然的判别性能。本文利用稀疏表示这一独特的优越性实现对车标的自动识别。相关实验结果表明，基于稀疏表示的车标识别方法对于车标中存在的污损、光照、部分遮挡等情况具有很强的鲁棒性。本文的主要研究内容和成果如下：

(1)、对稀疏表示理论进行深入研究，表明了车标图像可以表示为训练样本中多个原子的线性组合。由于原子的特征与车标图像的某些局部特征有着一定的相似性，当相似程度越高时，对应表示系数的值就会越大，反之越小，从而产生了对整幅车标图像的稀疏表示。因此利用稀疏表示对车标进行识别是可行的。

(2)、对车辆图像进行预处理。本文首先对车辆图像进行增强、倾斜校正、归一化、灰度化及中值滤波等预处理，再根据车牌位置先验知识确定车标的粗定位区域。与现有的车标识别方法不同，本文方法只需要知道车标的粗定位区域就可以实现对车标的自动识别，避免了车标定位不准确而给识别结果造成的影响。

(3)、提出基于稀疏表示的车标识别方法。在车标粗定位区域中，利用大小适中的滑动窗口获取测试样本图像，将其描述为混合字典的线性组合，通过最小范数方法求解稀疏表示系数。最后利用稀疏集中指数（Sparsity Concentration Index，SCI）对车标的有效性进行判别，并利用重构残差对车标进行识别。

大量实验表明，本文提出的基于稀疏表示的车别方法是合理的，具有较高的实际应用价值。

**关键词：**车标识别；稀疏表示；学习字典

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# Abstract

Vehicle logo recognition (VLR) which relate to computer vision, pattern recognition and image processing and so on, is one of the focus of Intelligence Traffic System. Most of the existing VLR methods need accurate vehicle logo location, but there is no effective method to accurately locate the logo which is subject to illumination, corrosion and part occlusion. It has a great influence on the recognition rate and makes the existing VLR methods restricted in practical applications.

Since the problem of vehicle logo location has affected the recognition rate, VLR based on sparse representation is proposed in this paper. Sparse representation can represent a signal concise, and the most concise representation has a natural discriminative performance, the unique performance of sparse representation can be used for recognizing vehicle logo automatically. Experimental results show that the proposed method is robustness to corrosion, illumination and part occlusion. The main research contents and results are as follows:

(1) Research the theory of sparse representation, it indicates that test vehicle logo image as a linear combination of some atoms of the training samples. The features between atom and some parts of the logo are similar, the more similar, the greater the corresponding coefficient is, as a result the whole logo has a sparse representation. Thus, sparse representation can be used for VLR.

(2) Vehicle image preprocessing. Firstly, many methods include enhancement, tilt correction, normalization, gray processing and median filtering are used for vehicle image processing, then, locating the coarse logo area through the position of license plate. Unlike existing VLR methods, the proposed method can identify the logo automatically once the coarse logo area is known, it avoids the impact on recognition results caused by inaccurate location of vehicle logo.

(3) VLR based on sparse representation is proposed in this paper. In the coarse

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vehicle logo area, the sliding window with right size is used for obtaining the test sample. Then, representing the test sample as a linear combination of training samples, and compute the sparse coefficients by  minimization. The sparsity concentration
index is used for validation, and the residual is used for identification. Numerical experiments show that VLR based on sparse representation is reasonable and has great practical values.

**Keywords:** vehicle logo recognitionsparse representationdictionary learning

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